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# Site Analysis of Knee Joint Injuries in Games Based on Deep Learning and Fusion Networks

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**ABSTRACT**

*By applying deep learning, we can better understand knee joint injuries that may occur in ball sports. This method can help us prevent these injuries more effectively and provide better protection for our athletes. This study developed a deep learning technique based on multiple modalities to identify common, major, and meniscus tear injuries, achieving rapid and accurate diagnosis. Additionally, it effectively categorizes the affected organs into different lesions based on their shape, size, and function. Experimental results demonstrated that the model accurately reflects the changes in the ROC curve, with an AUC change rate of 97.89% in normal anterior cruciate ligament tear or meniscus tear situations, significantly outperforming other methods and providing high accuracy.*

**Keywords**: Deep Learning, Knee Joint Injury, Multi-Modal, Feature Fusion

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## 1. Introduction

Ball sports have become widely beloved, with a wide range of sports, from traditional football to modern tennis, each with its characteristics. However, the knee joint is highly vulnerable in ball sports and can lead to serious consequences such as muscle strain, fractures, muscle atrophy, and ligament injuries. In the past, due to technological limitations, relying solely on medical knowledge and experience for diagnosing knee joint injuries in ball sports was insufficient, leading to shortcomings such as subjectivity, low accuracy, and lack of credibility. However, through in-depth analysis and research, we can better understand and take measures to reduce the risk of injuries for athletes [1]. Researchers are developing new, accurate technologies to effectively detect knee joint injuries in ball sports, which has garnered widespread attention in academia and practice. In recent years, research and exploration in deep learning have made significant progress, with its achievements widely applied in computer vision, automated programming, biomedical information data analysis, and other applications [2]. Especially in biomedical image data analysis, deep learning has provided more accurate ways for clinical detection, treatment, and prevention. To better understand knee joint injuries in ball sports, deep learning will assist us in finely detecting and diagnosing these issues [3]. We hope to aid in diagnosing and treating these problems effectively. In this development, we will use deep learning algorithms to identify damage to the knee on the field and use this information to understand these issues better. We will also rigorously test the accuracy of these algorithms to suit our work needs better [4]. Through this research, we can better understand the stress on knee joints in ball sports and better guide athletes' training to further improve their physical and mental conditions. Additionally, this research will positively impact the clinical practice of deep learning technology and provide important reference for related scientists. Through this study, we can offer a new method and approach for site analysis of knee joint injuries in ball sports, thereby enhancing athletes' physical health and sports performance. Moreover, this research can also provide valuable exploration and reference for applying deep learning technology in medical image processing.

## 2. Related Work

The knee joint consists of multiple tissue structures, including ligaments, articular surfaces, muscles, and tendons. It is one of the most complex and susceptible joints to injuries in the human body. As a common type of bone injury in clinical settings, knee joint injuries often occur in the meniscus, knee ligaments, etc.; patients usually exhibit varying degrees of swelling and pain. With the widespread use of X-rays, CT scans, MRI, and other imaging techniques, the accuracy of diagnosing knee joint injuries has significantly increased, providing objective evidence for early clinical treatment. Knee joint magnetic resonance imaging (MRI) has high soft tissue resolution, enabling it to capture richer image information. MRI images from different orientations, such as sagittal and axial, can comprehensively explore knee joint soft tissues and surrounding structures, obtaining detailed and accurate images. Therefore, MRI examination demonstrates high accuracy in the clinical diagnosis of anterior cruciate ligament tears and meniscus tears.

In recent years, knee joint MRI has become the preferred method for diagnosing knee joint injuries. An automated system for analyzing knee joint MRI images can screen high-risk patients and assist clinicians in making more accurate diagnoses. Traditional medical image analysis mainly employs methods such as edge detection, texture features, morphological filtering, shape modeling, and template matching. For instance, Ebrahimkhani et al. used a grey-level co-occurrence matrix to extract texture features of breast tissue, while Xie et al. used colour histograms to extract colour features of retinal images [5]. The multidimensional and multi-plane characteristics of MRI images limit the application of traditional medical image analysis methods to knee joint MRI [6], whereas deep learning methods can automatically learn multi-layer features, making them very suitable for assisting diagnostic medical imaging [7].

Deep learning methods have surpassed traditional medical image analysis methods in recent years and have made significant progress in knee joint MRI image analysis. Klontzas et al. proposed a novel voxel segmentation system that integrates three 2D CNN networks, each responsible for segmenting knee joint tibia cartilage in the *xy, yz*, and *zx* planes of MRI 3D images [8]. Swiecicki et al. developed a deep learning-based, fully automatic system for detecting knee joint MRI cartilage injuries using two CNN networks. The first CNN network performs rapid segmentation of cartilage and bone, while the second CNN network assesses structural abnormalities in the segmented cartilage tissue [9]. Tiwari's team first proposed a deep learning model called MRNet for predicting knee joint injuries, which predicts common knee joint injuries through MRI images, thereby improving the quality of MRI diagnosis [10].

In this paper, by fusing multiple features from sagittal, coronal, and axial MRI images of the knee joint, three common knee joint injuries, namely anterior cruciate ligament tears, meniscus tears, and general abnormalities, are classified and predicted. The effectiveness and feasibility of the proposed method are validated through various comparative experiments. Deep learning technology is utilized to automatically identify and classify knee joint injury sites in ball sports and evaluate the accuracy and reliability of the algorithm. This research provides a more accurate and reliable approach and tool for analyzing knee joint injury sites in ball sports.

# 3. Prediction Model Design

## 3.1 Construction of Multimodal Feature Fusion Algorithm

When dealing with knee joint MRI images, we can use two different techniques: traditional data mining techniques, which only capture basic boundary conditions such as contours, structures, colors, and spatial positions. In contrast, using Convolutional Neural Networks (CNN) for data mining can extract more abundant subtle differences, thereby obtaining more accurate data [11,12]. Both basic linguistic knowledge and more profound understanding are crucial in diagnosing knee joint diseases. Therefore, we study and develop a new multimodal feature fusion network to better identify knee joint diseases. Using formulas 1 and 2 can better control the model's parameters, thus achieving more accurate results.

For the VGG16 network model, we adopted a novel approach to obtain effective data. We extracted three parts from the model, namely HOG, LBP, and contact, and then used the PCA algorithm to select parts with higher contributions, referred to as transfer belts [13]. Subsequently, we applied a new method called pyramid fusion to combine the data of these parts, forming a more efficient model and thus obtaining more accurate prediction results.

$$E(x, h \mid \theta) = -\sum_{i=1}^{m} \beta_i x_i - \sum_{j=1}^{n} \alpha_j h_j - \sum_{i=1}^{m} \sum_{j=1}^{n} x_i \gamma_{ij} h_j \qquad (1)$$

## 3.2 Deep Feature Extraction

In recent years, with the advancement of technology, the use of Convolutional Neural Networks (CNN) in medical examinations has become increasingly common, showing remarkable performance. It can extract specific features from multiple images and possesses rich semantics and good stability and robustness. In 2014, the Visual Geometry Group at the University of Oxford first proposed the VGG16 network, consisting of five convolutional layers, with the first three layers serving as max-pooling layers and the remaining three fully connected layers. The VGG16 network uses the features from the last layer for classification, and its advantages are speed and low memory requirements [14]. However, its limitation is that it only focuses on the features of the last layer in the deep network, neglecting the features of other layers. Nevertheless, the fusion of multiple information can improve the accuracy of diagnosis to some extent. Since shallow layers in convolutional neural networks can learn more general low-level features, such as basic grayscale and edge information, deeper layers can capture more detailed features. Therefore, this study adds a Top-down structure based on the VGG16 network, gradually building the extracted feature layers into a feature pyramid and performing pixel-wise fusion through formula 3.

$$y^{(k)} = \gamma^{(k)} \hat{x}^{(k)} + \beta^{(k)} \qquad (3)$$

### 3.3 Multi-modal Feature Adaptive Fusion

Since both traditional and deep features have high dimensions, concatenating these features would result in longer computation time and higher computational costs. Therefore, we need to adopt a new approach to reduce the dimensionality of multi-modal features while effectively preserving the interactions between different modalities. To achieve this, we designed a novel multi-modal feature fusion module that combines a hidden layer with a neuron count lower than the feature dimension and a Sigmoid layer. This design allows for lower computation time, reduced computational cost, and effectively reduces the complexity of the fusion process. By utilizing the structure of the Sigmoid layer and the hidden layer, the model's accuracy can be significantly improved, enabling effective training of the model, as shown in Figure 1. The Sigmoid layer can transform the model's data into values within the range of (0, 1), better simulating real-world scenarios.

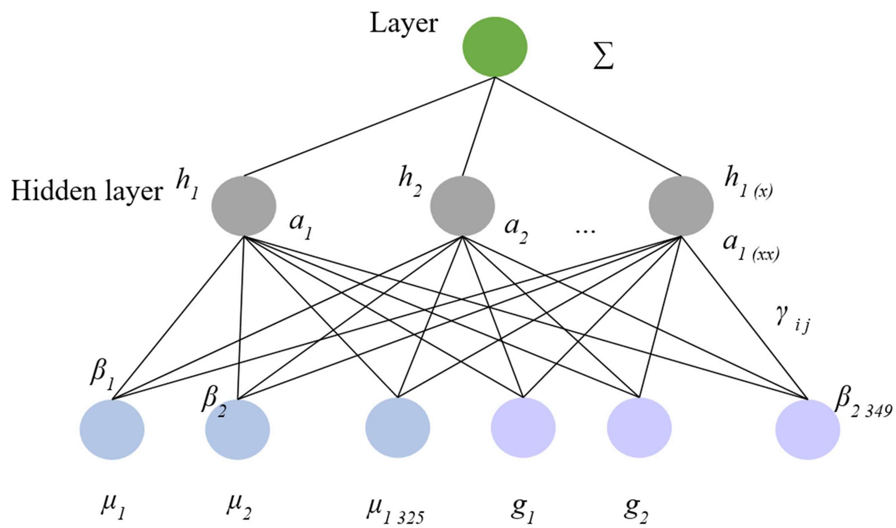


Figure 1. Multi-modal Feature Fusion Network Process Diagram

## 4. Experimental Design and Analysis

### 4.1 Experimental Design

In this experiment, we utilized a computer system with a 3.4GHz, 16-core AMD 1950x processor, 64GB GPU, and 12GHz GPU, as well as NVIDIA TITAN-V's video memory. Additionally, we employed Python for program development and utilized various computer vision libraries like OpenCV to support program execution. Using Pytorch as the foundation, we could efficiently construct, train, and make corresponding predictions. Furthermore, we utilized the Adam optimizer to effectively improve the model's convergence stability and achieve better classification performance. We lowered the learning rate to 1E"5, applied a weight decay of 0.01, and conducted experiments over 50 epochs. In this experiment, we trained and validated our proposed network model by analyzing publicly available knee joint MRI competition data. Our main objective was to enhance the reliability of our results through testing. We typically measured the performance of each model based on metrics such as Accuracy, Recall, and Area Under Curve (AUC). AUC value is an important metric to measure the precision of the model, reflecting the accuracy of the ROC curve, usually represented by the curve's height (y=x), with values ranging between 0.5 and 1. Therefore, the size of the AUC value can affect the model's accuracy and ultimately impact the final results. With continuous improvement in AUC, the accuracy also increases. This study used a dataset of 1370 knee joint MRI and MRNet images collected by Stanford University Medical Center. These images revealed abnormalities in 80.6% of cases (1104 examples), including 319 cases of anterior cruciate ligament tears, 23.3% of cases with meniscus tears, and 508 instances showing abnormalities. Among 194 cases, 38.2% exhibited dual tears, i.e., anterior cruciate ligament and meniscus tears. To better study this situation, we conducted sagittal-weighted sequence analysis, coronal-plane analysis, and axial-weighted sequence analysis for these cases. The number of sequences for each case ranged from 17 to 61, with an average of 31.48 sequences and a standard deviation of 7.97 sequences, providing rich data. Suppose the multi-modal feature fusion network includes all the sagittal, coronal, and axial weighted sequences. In that case, it will increase the hardware burden and runtime and lead to significant differences in feature expressions among different sequences, thereby reducing prediction accuracy. Through systematic analysis, we established a series of diverse models to handle various situations, including abnormalities, anterior cruciate ligament tears, meniscus tears, and sagittal, coronal, and axial plane conditions.

## 4.2 Experimental Results

Through in-depth analysis of MRI images, we found that feature extraction is crucial for classification and prediction, significantly improving the accuracy of the results. However, relying solely on texture and edge information from MRI images, our research results showed that the accuracy for meniscus tear diagnosis was only 69.17%, far below the practical application level. Therefore, we need more technical means to support our research. By comparison, the application of deep learning techniques in knee joint MRI image diagnosis demonstrated outstanding results. Its accuracy, reliability, and AUC value have greatly improved, especially in the task of abnormality prediction, where its reliability can reach 97.89%, or even exceed 76%. This indicates that it can detect positive lesions accurately, quickly, and reliably, bringing great convenience to clinical doctors. The significant improvement in AUC value enables it to resist bias effectively. Utilizing the meniscus-related region images and training them through a three-level connected residual network for meniscus tear grading prediction. As shown in Figure 2, the training was repeated for a total of 120 rounds, and after 80 rounds, it reached a near-convergence state, with a training time of approximately 3 to 10 minutes. The evaluation results for various class predictions were observable, and by using the algorithm proposed in this paper for estimation, each class achieved high identification accuracy.

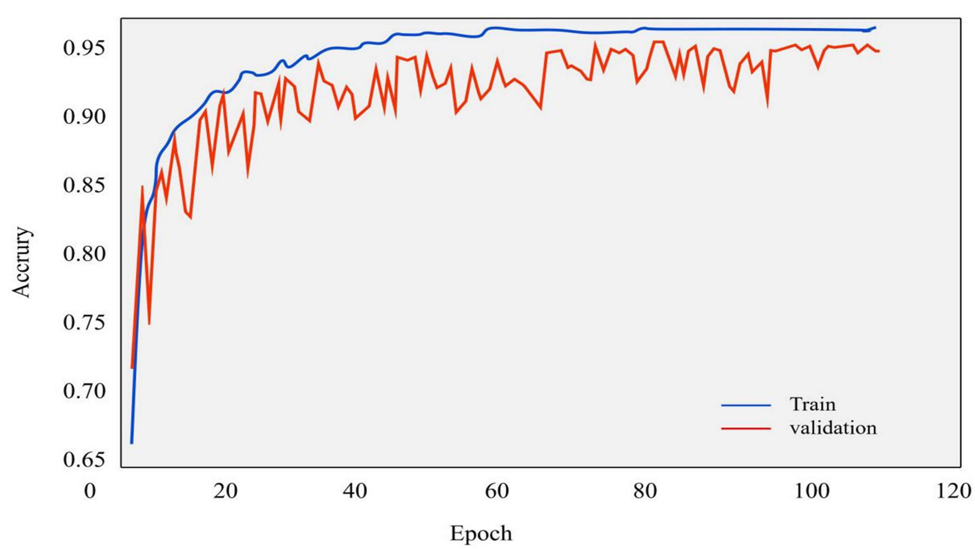


Figure 2. Training Accuracy Curve

In this paper, the model incorporates low-level semantic information into the convolutional neural network, enriching the feature representation of the model. As shown in Figure 3, our model (Ours) results indicate that after fusing traditional features with deep learning features, all performance metrics have been improved to a certain extent, especially BLEU. In the tasks of abnormalities, anterior cruciate ligament tears, and meniscus tears, as Eochsd increases, the BLEU values gradually increase to 30, 29, and 28, respectively. This result aligns with the knee joint structure, where the meniscus is located between the lateral condyles of the tibia and femur. In contrast, the anterior cruciate ligament is outside the knee joint's synovium. Therefore, the experimental results in this paper have a certain level of scientific validity.

# 5. Conclusion

In ball sports, knee injuries are prevalent, which not only pose a threat to the physical and mental health of the athletes but also may jeopardize their professional careers. Due to the knee's unique shape, function, and stress state, the range and severity of the forces it experiences vary, which places higher demands on the medical field for better detection and treatment. We have developed a novel multimodal information fusion technique to identify better and differentiate knee joint injuries. This technique can help us better assess the condition of patients and provide more detailed information to their doctors. We used logistic regression to evaluate the reliability of this information and combined it with traditional information fusion to assist patients in selecting more appropriate medical treatments. Through systematic experiments, we have found that comparing the three modes and the in-depth exploration of the regression model demonstrate the effectiveness of our method in predicting knee joint injuries. In the future, we will explore other forms of MRI images and their connections with other data to achieve more accurate diagnoses. Through in-depth exploration of knee joint MRI, we can better help patients prevent various diseases early and more accurately assess their conditions. Therefore, our research results can help us better understand the situation of patients and assist them in regaining their normal vitality, thereby promoting progress in the medical industry.

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